HYBRID TRANSFER LEARNING MODELS FOR VIDEO ANOMALY DETECTION IN SURVEILLANCE SYSTEMS

SYNOPSIS

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1. INTRODUCTION

Advancements in Artificial Intelligence (AI) have greatly enhanced how machines perform tasks that once required human intelligence. Machine Learning (ML), a key part of AI, enables computers to learn from data and improve on their own. Deep Learning, a highly advanced form of ML, uses complex neural networks to handle data like images and speech. It excels in tasks such as classification, detection, and recognition in video processing, delivering high accuracy. Deep learning models, which use supervised, unsupervised, and semi-supervised learning, can be retrained for new applications, making them versatile for tasks like image classification and biomedical analysis.

Key deep learning techniques, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Generative Adversarial Networks (GANs), and Autoencoders, are essential in advancing video processing methods. CNNs are especially effective for image and video classification due to their feature extraction capabilities, while RNNs and LSTMs excel in sequence prediction, making them ideal for tasks like video captioning and recognition.

Transfer learning [1] involves adapting a model trained on one task for a related task, leveraging knowledge from the initial problem to improve performance in the new context. This technique often utilises large datasets like ImageNet, a vast visual database used as a benchmark in computer vision challenges. Pre-trained models, such as ResNet, VGG, UNet, etc are developed on these large datasets, extracting valuable features that can be applied to other tasks. Fine-tuning these models on smaller datasets enhances their performance, making transfer learning efficient and widely applicable in fields like image recognition and segmentation.

The primary goal is to enhance surveillance video security by detecting, segmenting, and identifying anomalies. The research focuses on reviewing anomaly detection methodologies and exploring their applications across various sectors. It compares the performance of different deep learning techniques to improve the effectiveness and accuracy of anomaly detection, aiming to create more robust security systems. Four models are analysed to ensure a thorough comparison, validate findings, and explore diverse approaches.

2. LITERATURE SURVEY

Balasundaram and Chellappan [2] developed a deep learning framework for real-time abnormal event detection in online surveillance videos by integrating motion and appearance features with an attention mechanism, demonstrating effectiveness in practical applications. Doshi and Yilmaz [3] introduced an "any-shot" sequential anomaly detection method that adapted to novel data without a predetermined number of normal examples, validated on benchmark datasets. In [4], Doshi and Yilmaz also addressed continual learning for anomaly detection, proposing a framework that updated models over time without catastrophic forgetting, enhancing adaptability in surveillance systems. Liu et al. [5] leveraged transfer learning from action recognition to improve anomaly detection accuracy in surveillance videos, while Murugesan and Thilagamani [6] introduced a Multi-Layer Perception Recurrent Neural Network (MLP-RNN) for efficient real-time anomaly detection, both validated on standard datasets.

Yan et al. [7] presented a graph-based approach using Graph Convolutional Networks (GCNs) to capture complex spatial-temporal dependencies for anomaly detection, showing efficacy on standard datasets. Doshi et al. [8] developed an online anomaly detection algorithm with controlled false alarm rates, emphasizing reliable detection in security-critical surveillance applications. Huang et al. [9] used deep contrastive learning to enhance feature separation for abnormal event detection, improving performance in industrial surveillance. Li et al. [10] and Ma [11] focused on spatial-temporal architectures, combining convolutional and recurrent neural networks for detecting abnormal events in surveillance videos, both highlighting the importance of accuracy in security measures.

Vu et al. [12] enhanced model robustness against noise and adversarial attacks through adversarial training techniques, while Li et al. [13] developed a real-time anomaly detection system using lightweight architectures and transfer learning for high detection accuracy. Park et al. [14] introduced a multi-stream convolutional network architecture to improve detection performance by fusing diverse spatio-temporal features. Malik [15] presented a multi-stream 3D convolutional network for unsupervised anomaly detection, effectively capturing spatial and temporal patterns. Zhang et al. [16] utilized transformer-based models to capture long-range temporal dependencies for accurate anomaly detection. Lastly, Chen et al. [17] proposed a method for crowded surveillance scenes, focusing on spatio-temporal feature extraction to improve detection performance in densely populated

environments. Wang et al. [18] introduced an adaptive anomaly detection framework for surveillance videos that outperforms static models by continuously updating the detection model based on user feedback and environmental changes.

3. PROBLEM DEFINITION

Video anomaly detection is essential for identifying anomalous activities in surveillance footage to enhance public safety. Therefore, there is a need for efficient and accurate hybrid deep learning models capable of automatically detecting and analysing these behaviours in video surveillance. These models must leverage sequential data, improve segmentation, and identify spatiotemporal dependencies to address the limitations of current methods. The proposed work is to ensure better generalisation and reliability in real-world applications, overcoming issues such as overfitting and poor performance in complex environments.

4. OBJECTIVES OF THE RESEARCH

The following are the main objectives of the research:

- To develop efficient and robust hybrid models for detecting and analysing anomalous behaviour in video surveillance, by utilising video data.
- To expand the video anomaly detection model by focusing on segmentation, to improve accuracy and reduce overfitting.
- To enhance anomaly detection in low-resolution video by developing a hybrid CNN model that identifies spatiotemporal dependencies and reduces noise.

5. RESEARCH METHODOLOGIES

The experiments were conducted with the UCSD Dataset [19], created by the University of California, San Diego in 2008, which is a widely recognised benchmark for Video Anomaly Detection (VAD). Captured by a stationary, elevated camera overlooking pedestrian walkways, the dataset varies in crowd density from sparse to highly congested. It features normal pedestrian behaviour, with anomalies arising from non-pedestrian entities or unusual pedestrian movements, such as bikers, skaters, small carts, and people crossing walkways or moving on the surrounding grass. Notably, the anomalies occurred naturally, with no staging involved.

The dataset is divided into two subsets, each representing a different scene and containing video clips of approximately 200 frames:

- **UCSD Pedestrian 1 (Ped 1):** This subset includes 1,307 training frames and 231 testing frames.
- **UCSD Pedestrian 2 (Ped 2):** This subset includes 2,550 training frames and 2,010 testing frames.

The following system requirements were followed during implementation NVIDIA GEFORCE RTX 3050 GPU, an 11th Gen Intel Core i7, 3.30 GHz processor, 16 GB of RAM, and a 512 GB SSD, 64-bit Operating System, Windows 11.

5.1. Hybrid ResNet-50 And LSTM Approach for Effective Video Anomaly Detection in Surveillance Systems

In this phase, a hybrid framework combining ResNet-50 and LSTM enhances video anomaly detection by leveraging their strengths in spatial feature extraction and temporal modelling. ResNet-50, a deep convolutional neural network with 50 layers and skip connections, addresses the vanishing gradient problem and excels at extracting high-level spatial features from video frames. LSTM, a recurrent neural network architecture, complements this by utilising memory cells and gating mechanisms to capture long-range temporal dependencies and classify frames as normal or anomalous. The input video frames are resized to 256×256 pixels and processed with ResNet-50 for spatial feature extraction, followed by LSTM for frame categorisation, supported by CNNs for initial label generation, ensuring accurate and efficient anomaly detection. The integration of LSTM, CNN, and RNN architectures enhances the robustness and precision of the classification process.

The integration of ResNet-50 and LSTM improves accuracy, robustness, and generalisation by incorporating both spatial and temporal cues, making the model effective for applications such as surveillance, industrial monitoring, and critical event detection. The combination of these architectures ensures robust video frame classification, enhancing both precision and efficiency. However, the model may be susceptible to overfitting, which can impact accuracy and efficiency.

5.2. Anomalous Behaviour Detection and Analysis in Video Surveillance using CNN and Modified YOLOv4 Model

In this stage, the model for video anomaly detection is constructed through a multi-step process, starting with the conversion of video data into frames. These frames are analysed and trained using a Convolutional Neural Network (CNN), optimised with the Adam algorithm. The testing process involves several stages to detect anomalous behaviour. Histogram Equalisation is applied to the frames using the Cumulative Distribution Function (CDF) to normalise image pixels. The Euclidean Distance Tracker calculates the standard Euclidean distance between vector images and Image Euclidean Distance (IMED), taking into account the metric matrix and pixel distances. Threshold functions are applied to manage pixel values, including hard, soft, and controlled soft thresholds. For object detection, post-processing techniques are employed to remove noise and update the background model. Non-Max Suppression is used to suppress smaller gradient magnitudes along gradient angles. Edge-based segmentation is carried out using the Prewitt algorithm to detect edges in multiple directions.

Anomalous behaviour detection is performed using an optimised YOLO (You Only Look Once) framework. YOLOv4, with its advanced feature extraction, feature aggregation, and multi-scale detection capabilities, is chosen for its high performance. The YOLOv4 architecture includes a Backbone for feature extraction. A Neck for enhancing feature representation, which includes a Path Aggregation Network (PAN) for improved localisation, Spatial Pyramid Pooling (SPP) for handling objects at different scales. And the Head portion consists of three detection heads for bounding box prediction, object scoring. In The Modified YOLOv4 model instead of using 3 YOLOv3 heads a YOLOv4 head is used which helps to enhance detection accuracy and efficiency, making it well-suited for real-time object detection tasks. The model, trained on only 100 frames over 10 epochs, risks overfitting and poor generalisation; thus, exploring hybrid approaches that leverage multiple techniques is necessary.

5.3. Enhancing Video Anomaly Detection with Improved UNet and Cascade Sliding Window Technique

This proposed model addresses the challenge of overfitting in video frame anomaly detection by introducing an Improved U-Net architecture tailored for this purpose. The U-Net, a Convolutional Neural Network (CNN) designed for image segmentation, features a U-shaped

structure with a contracting (encoder) path for capturing hierarchical features and an expanding (decoder) path for generating high-resolution segmentation masks. In this improved version, standard convolution layers are replaced with ConvLSTM layers, enhancing the model's ability to capture spatiotemporal dependencies within video data, particularly in the encoder. The model integrates Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and CNN architectures to improve video frame classification, boosting both accuracy and efficiency.

Preprocessing involves applying a Wiener filter to reduce noise by adaptively smoothing data based on local signal variance. For feature extraction, the Improved U-Net is used for segmentation, increasing accuracy and robustness across various applications. The ConvLSTM network is crucial for capturing both spatial and temporal information from video frames. For classification, the Cascade Sliding Window Technique (CSWT) is used to generate an anomaly score by shifting a window across frames, effectively identifying anomalies by highlighting regions where actual and predicted frames differ. The model demonstrates significant potential in improving video anomaly detection. Further research is needed to enhance image quality and reduce noise. This involves refining techniques to improve clarity and minimise noise interference, thereby strengthening the overall robustness of the approach.

5.4. Hybrid Anomaly Detection with Hierarchical Multi-Scale CNN Fusion with LSTM

In the proposed model, a Hierarchical Fusion of CNN and LSTM for Multi-Scale Anomaly Detection is designed for use with both high and low-resolution images, particularly in automating anomaly detection in surveillance videos for public security. It addresses the limitations of traditional algorithms by reducing noise and overfitting.

In the preprocessing stage, the Bilateral-Wave Denoise technique is employed to minimise noise while preserving edges, allowing for the decomposition of images into various frequency components. For feature extraction, the model uses a Hierarchical Multi-Scale CNN, where the final pooling layer is replaced with a Spatial Pyramid Pooling (SPP) layer to capture multi-scale features and reduce overfitting. Temporal features are extracted using LSTM with Global Average Pooling (GAP), which captures and averages temporal patterns and trends. For classification, the model flattens multi-dimensional feature maps into a one-dimensional vector, then applies a fully connected Dense layer to compute weighted sums and learn complex patterns. Finally, Softmax activation is used to convert raw scores into probabilities,

ensuring accurate categorical classification of anomalies. A PSNR above 40 dB signifies excellent quality, and the Hierarchical Multi-Scale CNN with LSTM, with a PSNR of 42.18 dB, shows outstanding image quality preservation and improved generalisation through techniques such as Spatial Pyramid Pooling, highlighting its strong potential for real-world applications.

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

The effectiveness of the introduced systems has been evaluated through the assessment of various metrics like Accuracy, Precision, Recall, F1 Score, AUC, PSNR and EER. Accuracy measures the model's ability to classify normal and abnormal events, while precision and recall focus on identifying true anomalies and minimising false alarms. The F1 Score balances precision and recall, while AUC evaluates the model's discriminatory power. The Peak Signal-to-Noise Ratio (PSNR) is a widely used metric to measure the quality of reconstructed images or videos compared to the original. These metrics address model complexity, speed, and real-time performance.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \tag{1}$$

$$Precision = \frac{TP}{FP + TP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ Score = 2 \times \frac{FN}{TP + FN} \tag{4}$$

$$AUC = \sum \frac{(TPR[i] + TPR[i+1]}{2} * FPR[i+1] - FPR[i]) \tag{5}$$

$$EER = \frac{FP + FN}{TP + TN + FP + FN} \tag{6}$$

True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) have been used to measure the above-mentioned metrics.

Table 1 presents the performance of the proposed models and their corresponding performance metrics. The performance evaluation revealed that the Multi-Scale CNN and LSTM model excelled across most metrics, with high accuracy (99.35%), precision, recall, and F1 Score, along with the highest PSNR (42.18 dB) and AUC (0.9985), indicating superior classification and image quality retention. The CNN and YOLO model achieved the highest accuracy (99.46%) but had a lower PSNR (22.34 dB). The ResNet-50 and LSTM model was

balanced in performance with high PSNR (28.55 dB) but the highest EER (14.5%). The UNet and CSWT model performed well overall, particularly in PSNR (35.04 dB), but had a lower AUC (0.908).

Table 1. Comparison of Performance for all Models

Performance Metrics	**CNN and YOLO**	**ResNet-50 and LSTM**	**UNet and CSWT**	**Multi-Scale CNN and LSTM**
Accuracy (%)	99.46	96.5	99	99.35
Precision (%)	99.24	96.5	97.3	99.35
Recall (%)	98.79	96.5	97.5	99.35
F1 Score (%)	99.26	96.5	97.5	99.35
AUC	0.9926	0.99	0.908	0.9985
PSNR (dB)	22.34	28.55	35.04	42.18
EER (%)	2.1	14.5	10.9	5.4

Figure 1a and figure 1b shows the performance of proposed models for Accuracy and Precision respectively.

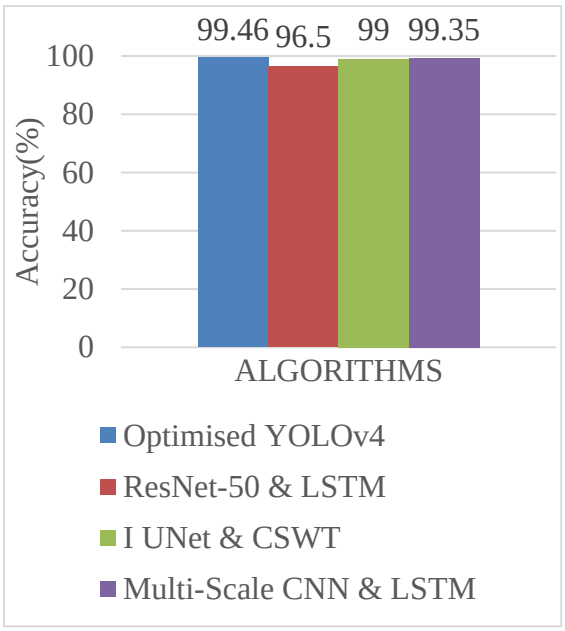

Figure 1a. Performance Comparison of Accuracy

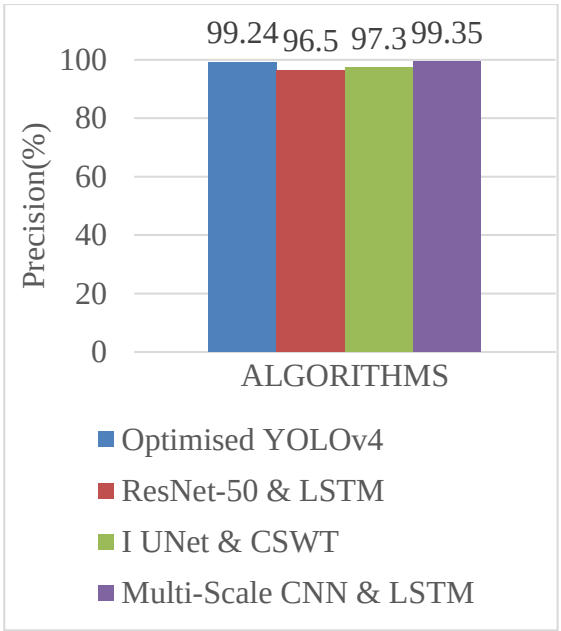

Figure 1b. Performance Comparison of Precision

Figure 2, Figure 3, Figure 4 and Figure 5 present the performance of the proposed models for metrics like Recall, F1 Score, AUC, PSNR and EER respectively. These bar charts visually compare the performance of four different model combinations across various metrics, showcasing that the Multi-Scale CNN and LSTM model consistently outperforms the others, especially in terms of PSNR and AUC values. While CNN and YOLO achieve the highest accuracy and F1 score, the ResNet-50 and LSTM model lags behind across most metrics.

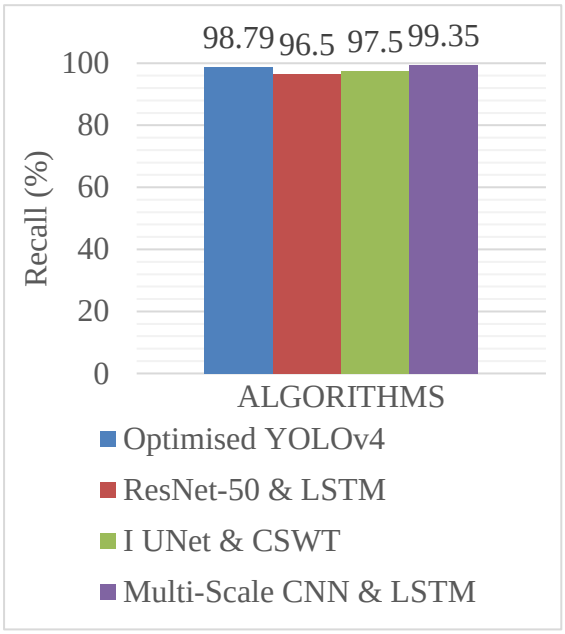

Figure 2a. Performance Comparison of Recall

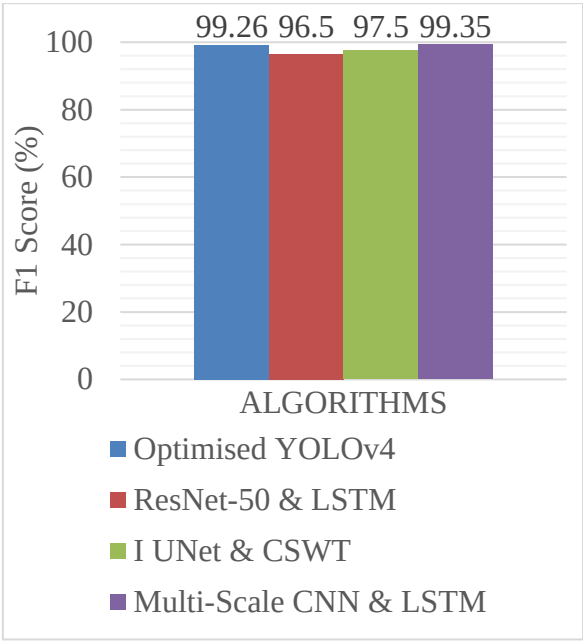

Figure 2b. Performance Comparison of F1 Score

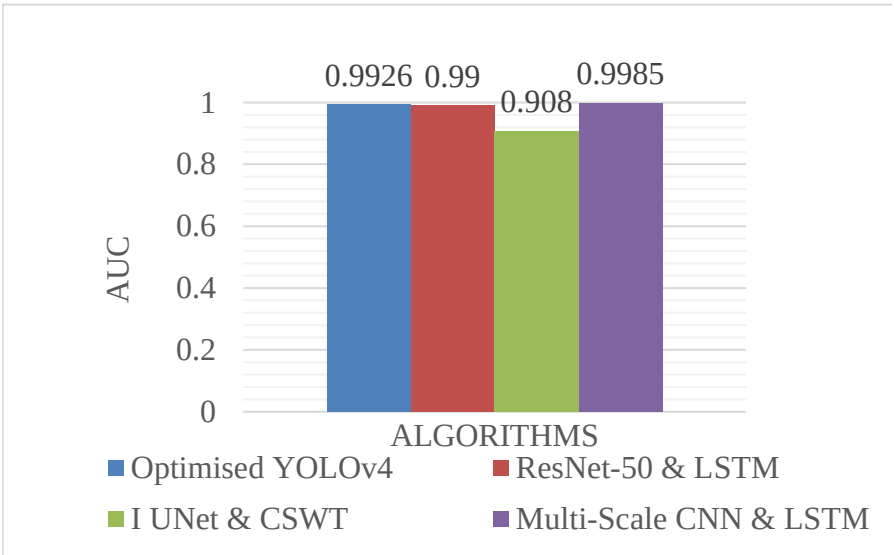

Figure 3. Performance Comparison of AUC for four Models

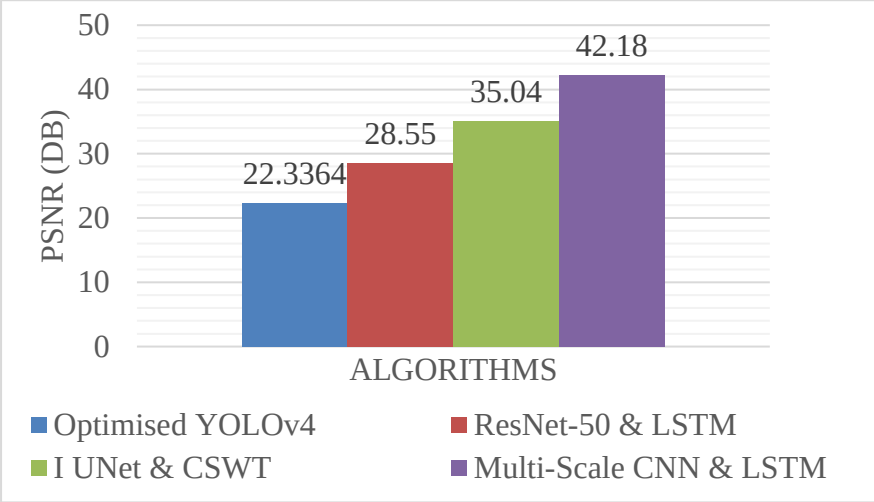

Figure 4. Performance Comparison of PSNR for four Models

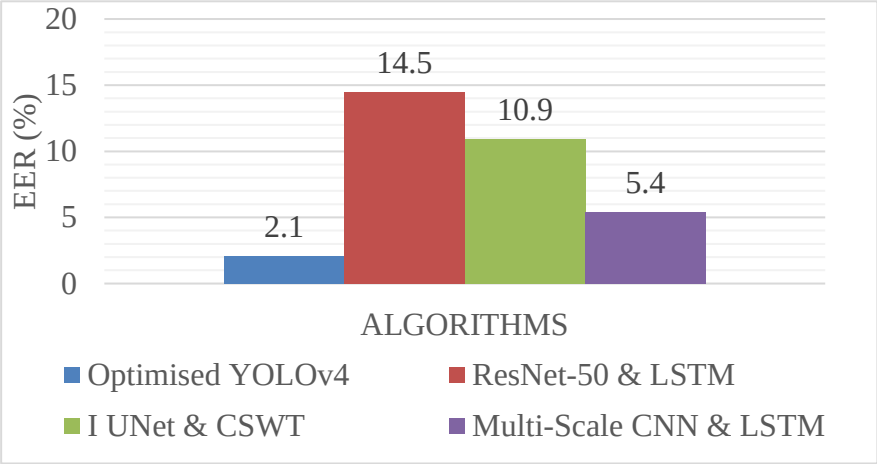

Figure 5. Performance Comparison of EER for four Models

7. CONCLUSION

Video anomaly detection (VAD) is increasingly crucial in today's world, where robust surveillance and security are paramount. As threats to public safety evolve, systems that can quickly and accurately identify suspicious activities in real-time are essential. VAD enhances surveillance by automatically detecting anomalies, reducing reliance on human monitoring, and enabling faster responses to potential threats, thereby preventing incidents and aiding investigations. Choosing the right VAD model is vital. The Hierarchical Multi-Scale CNN and LSTM fusion model stands out as the most versatile and high-performing option, boasting an accuracy of 99.35%, precision of 99.35%, recall of 99.35%, and an F1 Score of 99.35%. It also excels in image quality with a PSNR of 42.18 dB. The UNet and CSWT model follows with

an accuracy of 99%, precision of 97.3%, recall of 97.5%, and a PSNR of 35.04 dB, making it ideal for detailed data scenarios. The CNN and YOLO model, with the highest accuracy of 99.46%, precision of 99.24%, and the lowest EER at 2.1%, is best suited for real-time detection where speed is critical. Overall, the Multi-Scale CNN and LSTM model provides the most comprehensive solution for VAD, balancing accuracy, precision, recall, F1 Score, and image quality.

8. ORGANISATION OF THE THESIS

The thesis is organised as follows:

Chapter 1 reviews the evolution of video surveillance systems, from analogue to digital, and explores intelligent software and key algorithms for anomaly detection, including CNN, YOLOv4, ResNet-50, UNet, and LSTM networks. **Chapter 2** provides a literature review on video anomaly detection; that comprises deep learning approaches, current trends, and challenges, and contrasts classical methods with modern techniques. **Chapter 3** details a hybrid approach using ResNet-50 and LSTM networks for improved video anomaly detection, examining the integration of spatial and temporal data analysis and comparing it to standalone models. **Chapter 4** focuses on designing and testing a CNN and YOLO model for anomaly detection, evaluating its object detection capabilities and performance against other methods. **Chapter 5** explores new methods for video anomaly detection, including an improved UNet architecture and a cascade sliding window approach, assessing their accuracy and reliability. **Chapter 6** describes the development and evaluation of the Multiscale CNN and LSTM approach, highlighting its advanced feature extraction and temporal analysis, and providing a comparative analysis of the findings. **Chapter 7** tests the proposed systems using the USCD dataset, comparing their accuracy and efficiency in anomaly detection through key metrics and visual data representation. **Chapter 8** concludes with a summary of findings and provides the possibility of future work for further development.

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1. Krishnan, S. R., Amudha, P. (2023). “Hybrid ResNet-50 and LSTM Approach for Effective Video Anomaly Detection in Intelligent Surveillance Systems”, in *International Journal of Intelligent Systems and Applications in Engineering, vol 11 no 4,* pp.880–889. (Scopus Indexed).
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3. Krishnan, S. R., Amudha, P., “Enhancing Anomaly Detection in Videos using Optimized YOLO-based AI System”, in the *Journal of Intelligent and Fuzzy, Received Acceptance* on 15th April 2024. (Scopus Indexed)
4. Krishnan, S. R., Amudha, P., “Spatial-Temporal Anomaly Detection System with Improved-UNET” in the Journal *Informatics and Automation* Received acceptance on 18th July 2024. (Scopus Indexed)

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1. Sreedevi R. Krishnan, P. Amudha, “Study on Machine Learning Techniques for Video Anomaly Detection”, *Annual International Conference on Emerging Research Areas 2020: AICTE Sponsored Scopus Indexed International E-Conference on Computing and Communication Systems for a Fourth Industrial Revolution* organized by Amal Jyothi College of Engineering, Kottayam, Kerala, pp. 30, 14th to 16th December 2020, ISBN No. 978-93-5426-381-1
2. Sreedevi R. Krishnan, Dr P. Amudha, “Anomaly Event Detection using Machine Learning and Deep Learning Techniques: a Review” *International Conference on Emerging Trends in Industry 4.0 and Sustainable Concepts* organized by the School of Engineering, Avinashilingam Institute for Home Science and Higher Education for Women on 24th and 25th February 2023, ISBN: 978-93-5782-946-5
3. Sreedevi R. Krishnan, Dr P. Amudha, “Advancements in Video Surveillance: Trends, Applications, and Deep Learning Innovations” *6th International Conference on Computational Intelligence and Digital Technology (ICCIDT-2K24),* organized by Department of Computer Science and Engineering, Mangalam College of Engineering, Kottayam, Kerala on 3rd and 4th May 2024.